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Maintenance Analytics – The New Know in Maintenance

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Abstract: Decision-making in maintenance has to be augmented to instantly understand and efficiently act, i.e. the new know. The new know in maintenance needs to focus on two aspects of knowing: 1) what *can be* known and 2) what *must be* known, in order to enable the maintenance decision-makers to take appropriate actions.

Hence, the purpose of this paper is to propose a concept for knowledge discovery in maintenance with focus on Big Data and analytics. The concept is called *Maintenance Analytics (MA)*. MA focuses in the new knowledge discovery in maintenance. MA addresses the process of discovery, understanding, and communication of maintenance data from four time-related perspectives, i.e. 1) "*Maintenance Descriptive Analytics* (monitoring)"; 2) "*Maintenance Diagnostic Analytics*"; 3) "*Maintenance Predictive Analytics*"; and 4) "*Maintenance Prescriptive analytics*".

Keywords: **big data, maintenance analytics, eMaintenance, Knowledge discovery, maintenance decision support.**

1 INTRODUCTION

The dynamic global and local business scenarios put new demands on the decision-making processes in an organisation. The new decision-making processes need to provide enhanced capability for knowledge discovery online and in real-time. To increase the overall business efficiency, organisations need to implement a knowledge discovery platform in their core processes such as business, operation, and maintenance. Knowledge discovery is depended on availability if accurate and consistence data and information.

Today, enterprises are overwhelmed by managing data and its logistics. It can be testified that there is a growing gap between data generation and data understanding (Witten et. al, 2011). It can be considered that decisions are also becoming more complex with greater uncertainty, increasing time pressure, more rapidly changing conditions, and higher stakes (Busemeyer & Pleskac, 2009). The increased information needs and the development of Information and Communication Technology (ICT) have added velocity to everything that is done within an organization through transforming the business process into eBusiness (Lee, 2003). The knowledge discovery, which is an essentially a major aspect for maintenance decision support; is usually done by discovering special pattern of data, i.e. by clustering together data that share certain common properties (Wang, 1997).

Extensive application of ICT and other emerging technologies facilitate easy and effective collection of data and information (Parida, 2006; Candell et al., 2009). In maintenance, enhanced use of ICT facilitates the development of artefacts (e.g. frameworks, tools, methodologies and technologies); which aim to support maintenance decision-making. These artefacts also enable improvement of different maintenance approaches, such as; preventive maintenance and corrective maintenance. Furthermore, ICT provide additional capabilities, which can be used within diagnostic and prognostic processes. The prognostic and diagnostic processes in an enterprise can be facilitated through provision of proper information logistics aimed to support maintenance decision making through provision ICT-based solution for data processing and information management (Karim, 2008).

In the context of complex technical systems information logistics refers to: 1) time management, which addresses 'when to deliver'; 2) content management, which refers to 'what to deliver'; 3) communication management, which refers to 'how to deliver'; 4) context management, which addresses 'where and why to deliver' (Karim, 2008; Karim et al, 2009; Kajko-Mattson et al., 2011). However, ICT-based solutions to develop and establish an effective and efficient information logistics for prognostics and diagnostics in an enterprise can be materialised through eMaintenance solution (Söderholm et al, 2009). The provision of the right information to the right information consumer and producer with the right quality and at the right time is essential (Parida et al., 2004; Parida, 2006). Therefore, there is a need to integrate knowledge discovery with the maintenance decision support for effective decision making.

Decision-making in maintenance has to be augmented to instantly understand and efficiently act, i.e. the new know. The new know in maintenance needs to focus on two aspects of knowing: 1) what can be known and 2) what must be known, in order to enable the maintenance decision-makers to perform appropriate actions.

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The recent emerging technological and methodological achievements in knowledge discovery and knowing are changing the knowledge industry. Subsequently, the maintenance as a part of the new knowledge industry needs to be adapted to this new reality. The ongoing industrial digitalization provides enormous capabilities for industry to collect vast amount of data and information (i.e. Industrial Big Data), from various processes and data sources such as operation, maintenance, and business processes. However, having accurate data and information available is one the prerequisites in maintenance knowledge discovery. Beside the collecting data and information, another puzzle in the new maintenance knowing is to understand the patterns and relationships of these data collections.

Hence, the purpose of this paper is to propose a concept for knowledge discovery in maintenance with focus on Big Data and analytics. The concept is called '*Maintenance Analytics'* (MA). MA focuses in the new knowledge discovery in maintenance. MA addresses the process of discovery, understanding, and communication of maintenance data from four time-related perspectives, i.e. 1) "Maintenance Descriptive Analytics (monitoring)" focuses to discover and describe what happened in the past; 2) "Maintenance Diagnostic Analytics" focuses to understand why something happened; 3) "Maintenance Predictive Analytics" focuses to estimate what will happen in the future; and 4) "Maintenance Prescriptive analytics" which addresses what need to be done next.

2 MAINTENANCE DECISION-MAKING AND KNOWLEDGE DISCOVERY

Assets are complex mixes of complex systems, built from components which, over time, may fail. The ability to quickly and efficiently determine the cause of failures and propose optimum maintenance decisions, while minimizing the need for human intervention is necessary. Thus, for complex assets, much information needs to be captured and mined to assess the overall condition of the whole system. Therefore, the integration of asset information is required to get an accurate health assessment of the whole system, and determine the probability of a shutdown or slowdown. Moreover, the data collected are not only huge but often dispersed across independent systems that are difficult to access, fuse and mine due to disparate nature and granularity. Data relevant to asset management are gathered, produced and processed on different levels by different IT systems (Galar et al., 2012; Kans, 2013; Zhang and Karim, 2014) e.g. ERP (Enterprise Resource Planning) for business functions; SCADA (Supervisory Control and Data Acquisition) for monitoring process Nowadays the challenge is to provide intelligent tools to monitor and manage assets (machines, plants, products, etc.) proactively through ICT, focusing on health degradation monitoring and prognosis instead of fault detection and diagnostics. Maintenance effectiveness depends on the quality, timeliness, accuracy and completeness of information related to machine degradation state. This translates into following key requirements: preventing data overload, ability to differentiate and prioritize data (during collection as well as. Tools and machinery with satisfactory performance; efficient analysis tools, and planning tools. A performance killer is an input element to a process that performs poorly or hinders performance. In this context, a cost driver is an input element to a process that causally affects or drives costs which is tangible. A cost driver can be interpreted as an element that affects cost, or an element that increases costs considerably. Examples: Assets with high failure frequency and long downtime.

Some of the key parameters in the form of performance measures or indicators for Reliability Availability Maintainability and Supportability (RAMS) and Life Cycle Cost (LCC), etc. are continuously developed and applied for tracking maintenance activities.

Maintenance decision making, with multiple stakeholders largely depends on the maintenance failure data, RAMS and LCC data analysis for estimating the Remaining Useful Life (RUL) in order to perform effective business and maintenance decision making. Thus, supporting an effective maintenance decision making process needs a trusted DSS based on knowledge discovery. The process of knowledge discovery will essentially consists of; data acquisition, to obtain relevant data and manage its content; data transition, to communicate the collected data; data fusion, to compile data and information from different sources; data mining, to analyse data to extract information and knowledge; and information extraction and visualization, to support maintenance decision; as shown in Figure 1.

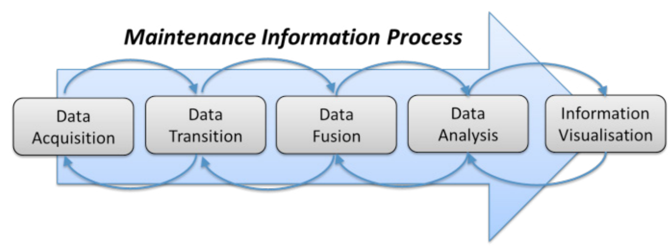

Figure 1. A generic knowledge discovery process.

The integration of data, recorded from a multiple-sensor system, together with information from other sources to achieve inferences is known as data fusion (Hall & Llinas, 2001). Data fusion is a prerequisite when handling data from heterogeneous sources or from multiple sensors. Knowledge discovery when applied for maintenance decision support uses eMaintenance concept for integrating the data mining and knowledge discovery. However, development of eMaintenance for industrial application faces a number of challenges which can be categorised into: 1) Organisational; 2) Architectural; 3) Infra-structural; 4) content and contextual; and 5) integration.

Organisational challenges mainly focus on aspects related enterprise resource management. Examples of these challenges are: 1) restructuring of the organizations involved in eMaintenance; 2) planning of resources (e.g. material, spare-part); 3) information management; 4) knowledge management; and 5) management of heterogeneous organizations.

Architectural challenges deal with issues related to the overall architecture of eMaintenance solutions. Some of these challenges are: 1) development of a framework for development of eMaintenance; 2) development of models for decentralized data processing and analysis; 3) development of service model for decentralized data analysis; 4) development